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Modelling conceptual change as foraging for explanations on an epistemic landscape

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Abstract

We discuss here conceptual change and the formation of robust learning outcomes from the viewpoint of complex dynamic systems, where students' conceptions are seen as context dependent and multifaceted structures which depend on the context of their application. According to this view the conceptual patterns (i.e. intuitive conceptions) may be robust in a certain situation but are not formed, at last not as robust ones, in another situation. The stability is then thought to arise dynamically in a variety of ways and not so much mirror rigid ontological categories or static intuitive conceptions. We use computational modelling in understanding the generic dynamic and emergent features of that phenomenon. The model shows how context dependence, described here through structure of epistemic landscape, leads to formation of context dependent robust states. The sharply defined nature of these states makes learning to appear as a progression of switches from state to another, given appearance of conceptual change as switch from one robust state to another.

Keywords: Conceptual change; concept learning; epistemic landscape; simulations

Introduction

Learning scientific knowledge where learners initial, intuitive concepts gradually change towards more scientific ones is known as conceptual change. Conceptual change as an expression for such learning emphasizes the clear transition or even revolutionary-like transformation of learners knowledge during the learning process (Duit & Treagust, 2003; Ozdemir & Clark, 2007; Rusanen, 2014). The recently suggested complex dynamic systems view on conceptual change instead of such a picture views students' conceptions as multifaceted structures which depend on the context of their application. In the dynamic systems view the conceptual patterns (i.e. intuitive conceptions) may be robust in a certain situation but are not formed, at last not as robust ones, in another situation. The stability is then thought to arise dynamically in a variety of ways rather than mirroring rigid preconceptions or static intuitive conceptions (Brown, 2014; Gupta, Hammer, & Redish, 2010; Koponen, 2013; Koponen & Kokkonen, 2014). What we think as intuitive conceptions may be in fact so strongly dependent on context, instructional settings and individual learning history that such conceptions should be approached as emergent cognitive epiphenomena, which are situational and mirror partially the targeted scientific models forming the basis of the design of instructional settings. In what follows, we refer to such epiphenomenal conceptual structures simply as students explanatory schemes. In this study we discuss how the dynamic systemic view may change our ideas how conceptual change may accrue from emergent robust learning outcomes. As a concrete example of learning we consider direct current (DC) electrical circuits and empirical results obtained in that context (Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017). In this case the target knowledge and learning situation can be modelled as learning a tiered structure of explanatory schemes, where students are expected to learn a simple set of concepts and relational schemes between the concepts. The model is highly simplified and idealized, but it shows how context dependence, described here through structure of epistemic landscape, leads to formation of context dependent robust learning outcomes. Due to sharply defined nature of these states, learning appears as a progression of switches from state to another, giving appearance of conceptual change as switch from one preexisting robust state to another, instead of gradual dynamic change.

Empirical cases modelled

The research of learning DC-circuits has revealed that the students tend to use very similar types of explanatory schemes. Some researchers of conceptual change attribute these schemes to pre-existing ontological commitments, while some others see them more context dependent and possibly even artefacts of the empirical research setting (Brown, 2014; Gupta et al., 2010; Koponen, 2013; Koponen & Kokkonen, 2014). Nevertheless, most empirical studies have revealed very similar collections of explanatory schemes although there are differences in details (see (Ozdemir & Clark, 2007; Gupta et al., 2010; Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017) and references therein). The empirical data used here as starting point consists of three different contexts I-III (Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017):

- I: Light bulbs in series. Two variants (a single light bulb and two light bulbs) in terms of the brightness of the bulbs are compared. This comparison consists of events e_1 and e_2.
- II: Light bulbs in parallel. The first variant is again involves a single light bulb. The second variant involves two light bulbs in parallel. Comparisons yield events e'_1 and e'_2.
- III: Comparison of the brightness of light bulbs in series (I) and in parallel (II). In the first variant, participants compare the brightness of light bulbs in series, and parallel circuits

to the one-bulb case only. In the second variant, participants compare series and parallel cases to each other. This yields events e_1'' and e_2''.

All six different types of events are referred to as an event set ε = e_0, e_1, e_2, e_0', e_1', e_2', e_0'', e_1'', e_2'', with e_0, e_0' and e_0'' representing observations of the brightness of a single light bulb in each context (the brightest light bulb). This set thus describes (formally) the task and how it was sequenced and how students progressed from context to I to III. In what follows ε is treated as exogenous variable describing the event set, scaled to range $\varepsilon \in [0,1]$ where 1 represent full set of events. Further details about the empirical setup, design and excerpts from the student interviews are reported elsewhere (Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017). When details are put aside, in all cases one finds similar types of explanatory schemes ,listed and characterised in Table I.

Table 1: The explanatory schemes m_k inferred from the empirical studies (Koponen, 2013; Kokkonen & Mäntylä, 2017).

Model	Description
m1	The battery as a source of electricity (current or voltage).
m2	m1+ components consume electricity (current or voltage).
m3	m2+ voltage/current over components creates/needs current/voltage.
m4	m3 refined as scheme based on Ohms law + Kirchhoffs laws KI and KII.
m5	m4+components consume electric energy/power (Joule's law)

Explanatory schemes m_1 and m_2 are well-known electric current-based intuitive explanatory schemes found in many empirical studies (Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017), while m_3 is partially correct explanation, which takes into account the role of components in determining the current. Finally, schemes m_4 and m_5 are complete and correct (scientific) schemes. The determination schemes D1 and D2 constraints (Kirchhoff's I and II laws, respectively) and D3 is relational scheme (Ohm's law) regulating the relationship between the pertinent concepts (voltage and current). A more detailed description of these cases and their representation are given elsewhere (Koponen & Kokkonen, 2014; Kokkonen & Mäntylä, 2017) and are not reproduced here. The structure of explanatory schemes can be schematically represented as in Fig. 1 as the generic tiered system, where more sophisticated explanatory schemes are at the highest tiers and the less sophisticated schemes at lower tiers can be seen as incomplete or partial versions of the higher tier explanatory schemes.

The simulation model

The task we discuss here involves five explanatory schemes with ascending complexity and can thus be represented as a tiered structure shown in Fig. 1.The tiered system of explanatory schemes can be represented as an epistemic landscape, which is an abstract representation of the explanatory power of explanatory schemes. Such descriptions have been previously used in studies describing the cognitive and social effects of discovery and knowledge foraging (Weisberg & Muldoon, 2009; McKenzie, Himmelreich, & Thompson, 2015). Learning is then described as foraging for best expalining scheme in that landscape, based on utility guided probabilistic selection of the best explaining scheme.

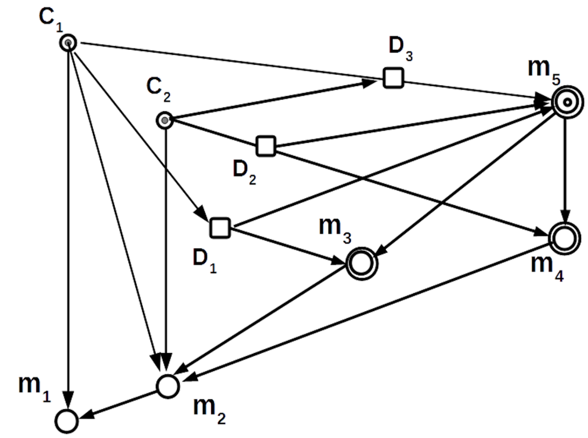

Figure 1: A Tiered system of five explanatory schemes. The different hierarchical levels consist of explanatory schemes m1 - m5 of ascending level of complexity and expanding coverage of explanatory power. The symbols C_1 and C_2 are concepts (current and voltage) entering the models m1-m5.

Epistemic landscape

A tiered system of explanatory schemes consists of schemes m_k, k=1,2,...,5, in which the hierarchical level k is defined according to the complexity of the scheme. More complex schemes require greater proficiency from the user of the scheme, such as mathematical proficiency in deriving predictions from the scheme or making deductions based on it. The utility of a given scheme can be seen as a trade-off measure between the scheme's complexity and the amount of events which the learner needs to explain. The scheme m_1 is simple and, thus, its utility for a simple set of events is high, but decreases for many events to be explained. The scheme m_5 is the most complex one and requires great proficiency. Because it is complex to use, it has low utility in simple cases, but its utility increases with accumulation of events.

The system of explanatory schemes, as far as the explanatory power of schemes for given set of events is in focus, can be represented in idealized form of epistemic landscape. The epistemic landscape is a simplified description how increased information (in form of events) gives cues to select a given model, and on the other hand, it describes how much proficiency is required in using the model. There is at present no detailed way to derive the epistemic landscape from the graph as described in Fig. 1 and the connection remains a qualitative one. With these restrictions, however, the epistemic landscape can be constructed by using utility functions $u_k(\varepsilon,\kappa)$, which describe the epistemic utility of schemes m_k. The detailed forms of the functions are, fortunately, not important here; it is enough that they can serve to describe the assumed generic features of the tiered system. Therefore, the mathematical description of the epistemic landscape adopted here is based on a set of suitably flexible functions. Convenient mathematical forms that are easy to use in simulations because the cumulative probability finction is invertible are provided by MinMax-distributions (Kumaraswamy-distributions) (Jones, 2009) as given in Table 1. The epistemic landscape thus consists of five manifolds of which Fig. 2 show the schemes with the greatest utility in a given region.

Table 2: The utility functions $u_k(\varepsilon,\kappa)$ forming the epistemic landscape. The normalization factors N_1-N_5 are defined so that maximum value of each utility function is 1. The functions $f_{n,m}(x) = x^m(1-x^{m-1})^{n-m}$ are MinMax-distributions (Kuwaraswamy-distributions).

State	Utility function
m_1	$u_1(\varepsilon,\kappa) = N_1 f_{n_1,m_1}(\varepsilon)\ f_{n'_1,m'_1}(\kappa)$
m_2	$N_2[a_1u_1(\varepsilon,\kappa) + a_2 f_{n_2,m_2}(\varepsilon)\ f_{n'_2,m'_2}(\kappa)]$
m_3	$N_3[b_1u_2(\varepsilon,\kappa) + b_2 f_{n_3,m_3}(\varepsilon)\ f_{n'_3,m'_3}(\kappa)]$
m_4	$N_4[c_1u_3(\varepsilon,\kappa) + c_2 f_{n_4,m_4}(\varepsilon)\ f_{n'_4,m'_4}(\kappa)]$
m_5	$N_5[d_1u_4(\varepsilon,\kappa) + d_2 f_{n_5,m_5}(\varepsilon)\ f_{n'_5,m'_5}(\kappa)]$

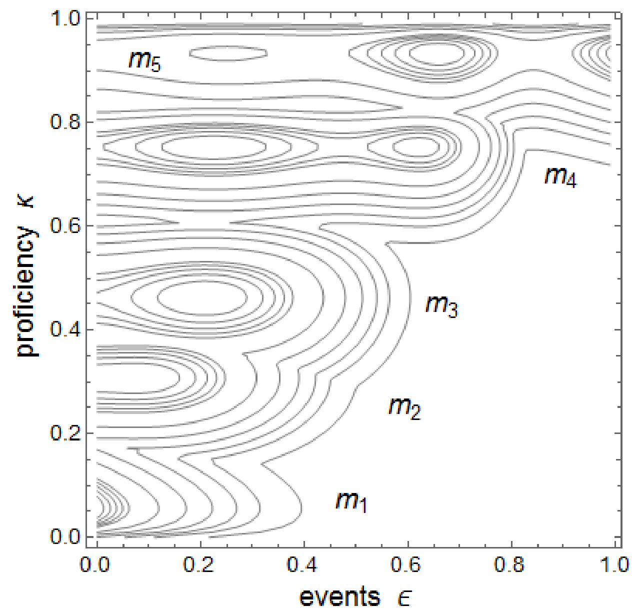

Figure 2: The epistemic landscape corresponding to explanatory models from m_1 to m_5 as indicated in space spanned by events consisting of events ε and learner's proficiency κ. The contours are shown for values 0.95, 0.90, 0.86, 0.82, 0.78, 0.74, 0.70, 0.67, 0.60, 0.55, 0.50.

Learning as foraging

The model of learning introduced here assumes that learning takes place as foraging for explanation schemes across the epistemic landscape. We assume that foraging is guided simply by the topography of the epistemic landscape, as a "hill climbing" (HC) in the direction of the steepest change of the gradient of the landscape (McKenzie et al., 2015; Weisberg & Muldoon, 2009). When exogenous parameter ε increases by $\delta\varepsilon$ (a new event or cue becomes available), the agent selects the most probable explanatory scheme from the neighborhood of its current state either by switching the state, "uphilling" by increasing the proficiency or, if more advantageous, "downhilling" by decreasing the proficiency. Proficiency is taken here as a skill-like property. A response to success and failure is modelled as logistic development (Steenbeck & Van Geert, 2007; Van Geert, 2014) of learner's proficiency during the learning process in form

$$\kappa \leftarrow \kappa \pm \mu\kappa(1-\kappa) \tag{1}$$

where μ is the effect of memory of success or failure. Here, success means that during foraging learner has upphilled, i.e. moved to direction of increased utility, failure, on the other hand, means that learner has downhilled, moved towards decreased utility.

Selection of explanatory scheme

The learners are assumed to select the best explanatory scheme m_k, one at a time, on basis how its utility compares to utilities of other schemes. The probability P_k that scheme m_k is selected is based on probabilistic decision theory (Laciana & Oteiza-Aguirre, 2014; Yukalov & Sornette, 2014) and is given as

$$P_k = \frac{u_k \exp[\,\beta u_k\,]}{\sum_{j\neq k} u_j \exp[\,\beta u_j\,]} \tag{2}$$

where β is parameter related to the *confidence* of choice, $\beta \ll 1$ indicating low confidence (i.e. high noise or randomness) and $\beta \gg 1$ high confidence (i.e. low noise or randomness). In what follows, we use $\beta = 5$ which represents high confidence.

Implementation of simulations

The control (exogenous) variable is event ε. The output (endogenous) variables are the selected explanatory scheme m_k and the learner's proficiency κ, which changes dynamically as a part of the learning process. The output variables depend on the parameters, which are the *confidence* β and *memory* μ.

The learning process as foraging across the epistemic landscape is simulated based on the probability of explanatory scheme selection P_k in Eq. (2). At each instant when the value of ε increases by $\delta\varepsilon$ (here $\delta\varepsilon$ = 0.01), it is decided whether: 1) the model switch happens, or 2) proficiency increases, decreases or remains unchanged. Both of these three steps are characterised by a set of probabilities, and event selection is carried out by the roulette wheel -method (Lipowski & Lipowska, 2012). In the roulette wheel -method a discrete set of N possible events k with probabilities p_k are arranged with cumulative probability $\Phi_k = \sum_{i=1}^{k} p_i / \sum_{i=1}^{N} p_i$. The event k is selected if random number $0 < r < 1$ falls in the slot $\Phi_{k-1} < r < \Phi_k$. In case 1) the probabilities p_k are given by Eq. (5) and $p_k = P_k$ with $k = 1,2,3$. In case 2) one has three probabilities $p_1 = P_{k'}(\varepsilon + \delta\varepsilon, \kappa)$, $p_2 = P_{k'}(\varepsilon + \delta\varepsilon, \kappa + \delta\kappa)$ and $p_3 = P_{k'}(\varepsilon + \delta\varepsilon, \kappa - \delta\kappa)$ for any given scheme $m_{k'}$. All simulations are carried out for equally distributed set of all initial values of κ, for 100 steps with $\delta\varepsilon = 0.01$ and $\delta\kappa = 0.01$ in a mesh of 100x100 points and for 9000 repetitions.

Results

The outcome of the simulations applied in case of learning the tiered theory structure is number density n_k of choice of given scheme m_k at given values of ε and κ. The number density n_k is related to likelihood that in an ensemble of students a given student holds the explanatory scheme m_k. In case a large set of students' explanatory schemes are collected in an empirical research the density n_k would correspond the distribution of how different finding are classified in different categories, categories then roughly corresponding the peaks in the density distribution, while the slight differences in empirically found categories would corresponding the diffuse spread of seen in the density distribution. This association of empirical findings is not exact, of course, but provides a close enough interpretation of the density plots. Note that all density plots are shown as contour plots as in topographical maps.

The shift to hold or select more advanced schemes during the learning (or training sequence) when ε increases from ε =0 (no events to be explained) to ε=1 (all events to be explained) is particularly clear when density n_k of selected schemes in the (ε, κ)-space is examined. Such density distributions n_k of preferred schemes are shown in Fig. 3 for strong (μ=0.05), intermediate (μ=0.02), and weak (μ=0.01) memory effects. Results are shown only for cases that initially have proficiencies $0.45 < \kappa < 0.55$ which represents a middle cohort of initial proficiencies, thus representing the assumed average student for which the learning task is designed. The results shown in Fig. 3 demonstrate how selection of given schemes k accumulate to certain regions, different from but close to those regions where utilities (see Fig. 2) have peak values. These regions are shown as dark color in the figures, the darker the shade the higher the density. The dark regions where densities accumulate are the robust outcomes of learning. This behaviour is due to dynamic effects of foraging for best explanatory schemes in the epistemic landscape and how memory affects the development of proficiency.

The density distribution shows directly how likely a selection of given explanatory scheme is in comparison to other schemes. When the memory is weak (μ = 0.01) the low-level schemes m_1 and m_2 are likely to be selected throughout the learning sequence. In addition, scheme m_3 is present throughout the learning sequence because it is the most preferred initial scheme for mid-cohort learners. When memory increases from μ =0.01 to 0.05 the dynamic evolution becomes more interesting. In the intermediate stage of learning (stage II) scheme m_4 begins to compete with m_3 and finally, in the end of the learning stage scheme m_5 is dominant. For the highest memory μ=0.05 the development becomes very predictable. Schemes m_1 and m_2 are likely choices only at low proficiencies, and finally, in the end of the training sequence ε ¿ 0.6 the scheme m_5 is dominant. For high memory-effects and high confidence the robust learning outcomes are sharply defined, island- like and give expression of well-focused explanatory schemes with no overlap with other explanatory schemes. The overall picture is then that when new event becomes available, learner switches to better explaining schemes towards the end of the learning sequence. This is the successful learning path.

In high memory region, however, the polarization of learning outcomes happens; with increased preference of high level schemes m_5 also the preference for low level schemes m_1 and m_2 tend to increase. This is due to fact that success and failure affect in similar way and have equally strong memory-effect.; success feeds success but similarly also failure feeds failure. Of course, were the memory effect asymmetric, stronger memory effect for success than for failure, such polarization would disappear.

Discussion and conclusions

In the complex systems view of conceptual change suggested here the formation of robust learning outcomes accrues from foraging on epistemic landscape, which represent the target knowledge as it is contained in the designed learning task. The interplay of learner's cognitive dynamics and the target knowledge as it appears in the design of the learning tasks leads to formation of stable and dense regions of preferred explanatory schemes in epistemic landscape. The origin of these robust states is on the learning dynamics and how it interacts with the context (structure of the learning task). In some cases, depending on the learner's proficiency and the development of the proficiency, learning outcomes may match the target knowledge, but in some other cases, may fall short of targeted outcomes. However, even those states, which do not match the targeted states, are robust, thus giving impression of pre-existing conceptual states of learner, as assumed in traditional conceptual change models. Accumulation of densities n_k in certain regions are those areas, where empirical findings will be likely to associate the dynamically formed epiphenomenal robust state with a certain assumed misconception or pre-existing intuitive conception. If this interpretation is correct, the vision of conceptual change as switch between cognitively pre-existing static states to another needs to be revised and replaced by a more dynamic and fluid picture of dynamically formed robust but yet epiphenomenal states.

In the present study, the picture of conceptual change as

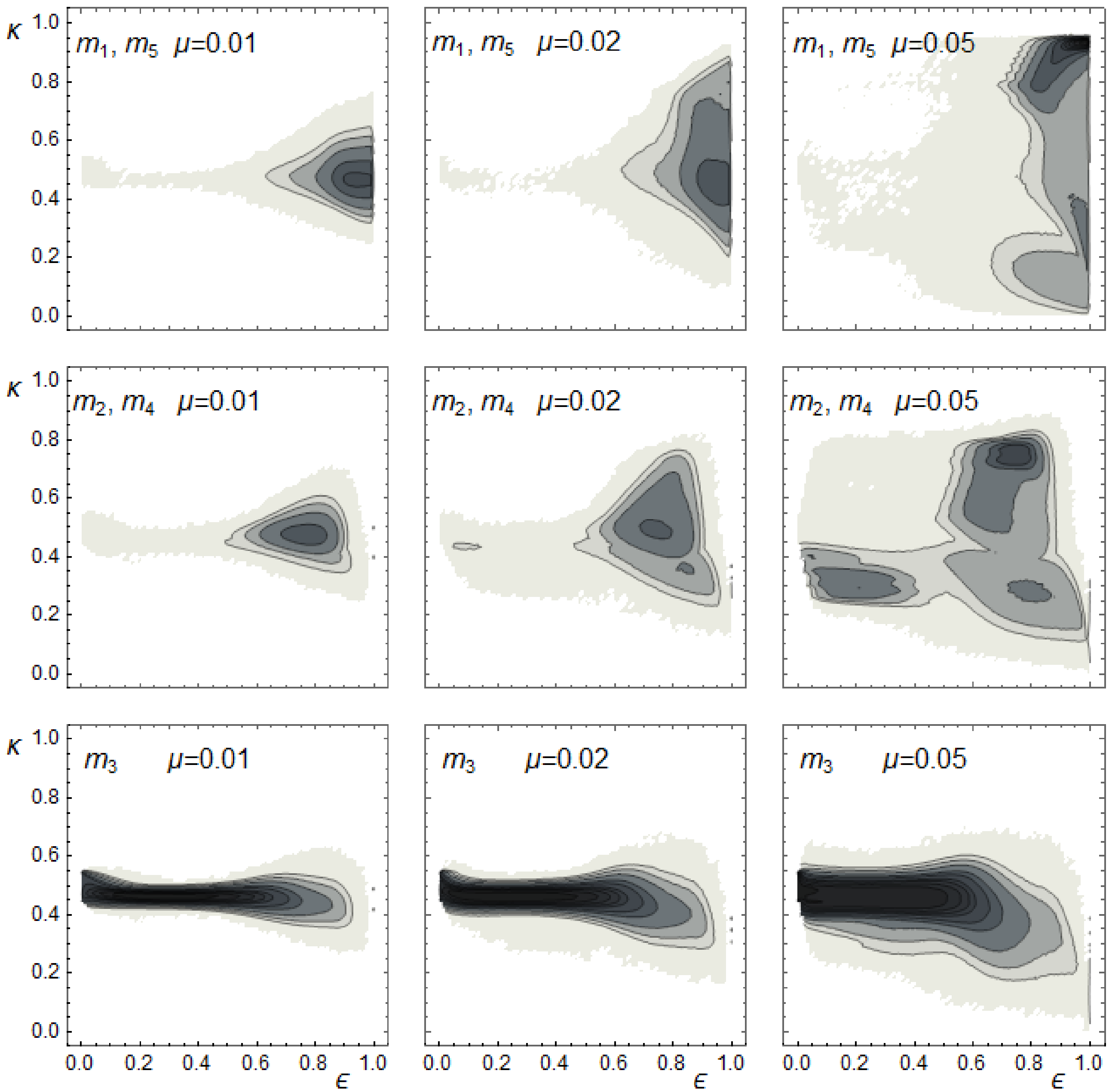

Figure 3: The effect of memory μ on explanatory scheme selection n when events unfold (described as an increasing number of events ε). The cases with memory μ=0.01, 0.02 and 0.05 are shown. The range $\kappa \in [0.45, 0.55]$ of initial proficiencies are considered (mid-cohort). The contours are shown for probabilities P = 0.80, 0.70, 0.50, 0.25, 0.15, 0.10, 0.05, 0.02, 0.01, 0.0050, 0.0025. The number of repetitions for each of 100x100 data points is 9000.

switch from intuitive conceptions to more scientific conceptions (or sometimes, to other intuitive conception) emerges as rapid but continuous dynamic development of one robust state to another state rather than as abrupt and discontinuous switch from one pre-existing static state to another. Moreover, such states are seen as epiphenomenal outcomes of interplay between learning dynamics and task design, rather than independent construct of mind, rooted in cognitively fundamental, e.g. substance-based ontological categories. The fact that for most of the training sequence there is little overlap between the different robust epiphenomenal states and periods of clearly continuous change are short, a picture of discontinuous switch from robust state to another is obvious. Superficially the course of events in the present model correspond the traditional view of conceptual change but the difference in interpretation of the underlying dynamics and nature of states in present view is fundamentally different from the traditional one; the present view strongly suggests that behind the observed behaviour is after all continuous learning dynamics and which, through designed epistemic landscape, is essentially context dependent.

In summary, the dynamic view provides fresh viewpoint on conceptual change and suggest new ways to conceptualise it. The results we have provided here are far from conclusive and are at best only suggestive, but we think that the view proposed here of learning outcomes as context dependent, dynamically robust but ultimately emergent epiphenomena deserves closer attention and prompts us to design very different empirical research settings. We expect that the main use of the abstract computational model as introduced here is on its potential uses in guiding attention in interdependencies of task structure and learning outcome, and in helping to focus on dynamic, time dependent features of conceptual change in empirical research settings.

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